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Productivity and Automation in Automotive Manufacturing: The Impact on Ohio Employment

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The supposed decline of the United States manufacturing industry has been a central topic of political concerns and research for decades. The classic story is that America's might in this sector was seen as the backbone of the economy and a central factor in the nation's economic dominance relative to the rest of the world. In light of this, it's easy to see how a decline in the manufacturing base has become such an important issue. In recent years, two main theories have emerged as to what is to blame for the loss American manufacturing jobs over the last two decades: trade agreements and improving technology (or automation). The general argument regarding trade is that the expansion of globalization in the last few decades, via trade agreements like NAFTA, have led to companies closing down American factories and moving production to other nations in order to take advantage of cheaper labor. While this certainly provides rich grounds for research, having inspired much already, this particular paper will instead focus on the impact of technology and automation. In this case, the argument proposes that technological advancements over the last 3 decades have caused a major shift in the workplace. The idea is that technology has dramatically improved productivity and efficiency, so much so that many jobs that were once performed by humans can now be performed by robotics or other technological systems. In this way, some workers have effectively become obsolete, leading to declining employment numbers due to lack of demand for actual human labor. Much research has been done on this topic as well, which will be discussed at length in the following section. This paper aims to make its unique contribution to the literature by looking specifically at the impact of technology on productivity in the automotive manufacturing sector, an important subset of the overall manufacturing sector (particularly to a certain geographic region).

The issue at hand in the research paper is, simply put: has technology been a driver of productivity growth in the automotive manufacturing industry in the US? If so, what has been the impact on the level of employment in this sector? More specifically, this paper will focus on the state of Ohio. The impact of technology on productivity and employment is of interest here because of the aforementioned body of research that exists on this topic for the manufacturing sector broadly. The answers to these questions will have large implications for future policy. Automotive manufacturing jobs have historically been some of the most central sources of employment for the American middle class. This is especially true of the "Rust Belt" region of the country, which historically is largely dependent on the manufacturing industry. Changes in the labor market for autoworkers stand to impact a significant portion of the population and economy, and it therefore stands to reason that this problem should be researched to consider what issues exist and how a proper policy response can be formulated.

Previous research lays the groundwork for this paper by providing a look at the effects of technology on the economy, workers, and the manufacturing sector generally. A 2011 piece from Erik Brynjolfsson and Andrew McAfee, entitled *Race Against the Machine: How the Digital*

Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy provides a general sense of the trends of technological advancement. In a summary paper published in 2012, the authors describe how they studied the impact of technology on jobs, skills, wages, and the overall economy in the wake of the "Great Recession." Their central argument is that the slow recovery from the recession is not fully explained by simple cyclical weakness in demand. Rather, they propose that technology has advanced at such a rapid pace that many workers have effectively been left behind. Computer-driven technologies are called a "General Purpose Technology" by the authors, on par with the steam engine, electricity, and the internal combustion engine in terms of ability to alter productivity. They believe that recent technological improvements (in tandem with those that are on the near horizon) essentially constitute a new industrial revolution, one that has rendered human labor obsolete in many tasks. The piece strongly supports the hypothesis of automation being a major job killer. While the authors do note that there are some areas in which humans still have the upper hand, such as problem solving and creativity, they urge serious consideration of this issue so that humanity can structure production in such a way as to take advantage of the technological revolution rather than lose the "race against the machine." It should be noted here that the evidentiary standards for popular books such as this are not quite as robust as those required for formal academic research. This is not to imply the conclusions are incorrect; however, the reason this piece is mentioned here is due to its role in increasing the popularity of this line of inquiry and promoting awareness of the general idea and its implications. For those reasons, it is worth including in this literature review.

Another 2011 piece by Fleck, Glaser, and Sprague gives potential insight into the relationship between productivity and wages. The approach taken is to examine trends in productivity growth compared to trends in compensation, both in the total nonfarm business sector and the manufacturing subset of this sector. What they found is that compensation tended to closely follow productivity for decades, with gains in wages matching the gains in productivity from 1947 until the late 1970s. However, beginning in 1980, a new pattern emerged. Productivity continued a steady rise, commensurate with previous trends. Compensation, however, began to lag; it still increased overall, but at a much slower rate than productivity. In the manufacturing industry, the results were more interesting – and more relevant to consider for this paper. Since 1980, productivity in manufacturing increased, at times at a rate even faster than in the preceding decades. However, real compensation effectively flat lined, experiencing little to no gains over the same time period. This stark finding helps provide some support for the hypothesis of automation, as it has been interpreted as evidence of a de-coupling of productivity and wages. In other words, lagging wages in the face of increasing productivity could show that technology is driving these improvements rather than worker skill – and therefore companies are replacing workers with machines. This also has the implication that the monetary gains from increased productivity are not accruing to workers, but rather, the owners of capital.

In 2014, authors Daron Acemoglu, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price took on the question of productivity in manufacturing in their 2014 paper *Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing.* Their research is similar to the purpose of this paper, although their focus is on manufacturing more broadly rather than a specific type of manufacturing. The authors looked to find whether technology has boosted productivity in US manufacturing. Initially using a measure of computer investments as a marker for technology use, they found little evidence of productivity growth (excluding computer-producing firms). However, upon switching their measure to account for usage of advanced manufacturing technologies, there was evidence of productivity growth throughout the 1980s and 1990s, will a tailing-off in the 2000s. They then turn their focus to discovering the source of this increased productivity – did it come from increased output, or fewer workers? This yielded interesting results. Analysis showed that, although output was actually declining relative to other industries, employment was actually falling at a faster rate. Thus, declining employment was responsible for the productivity gains. Though this could appear to support the idea of displacement by automation, the authors caution that the timing appears inconsistent with this conclusion. Employment losses occurred throughout the 1990s, but actually stopped into the 2000s – indicative of the previously mentioned tailing-off of productivity growth at this time. Therefore, the takeaway is that the so called "Solow Paradox" may not yet be resolved. Productivity gains from technology were mixed, and largely dependent upon the measure used. Though job loss did occur, the overall findings are not consistent with the automation hypothesis – at least not in US manufacturing.

The last paper which we will examine for background information comes from Acemoglu and Restrepo, published in 2019. In a sense, *Automation and New Tasks: How Technology Displaces and Reinstates Labor* picks up where the previous paper left off. Acemoglu and Restrepo attempted to deal with the conflicting ideas and conclusions regarding the impact of technology on labor by creating a model based on actual tasks performed. Their model was meant to show how machines can alter that balance. The authors explained that the introduction of new technology can impact labor in one of three ways. The first, called the Displacement Effect, occurs when machines take over tasks formerly performed by labor. The Productivity Effect is when a flexible allocation of tasks is possible, and automation can therefore increase productivity and boost demand for labor in non-automated tasks – put simply, the machines are so efficient that more people are needed to meet the increased demand for related goods whose production is not automated. Last is the Reinstatement effect, which occurs when technology creates new tasks in which labor has the comparative advantage; this effectively fights the displacement effect, as it means that increased technology usage will also result in an increase in the demand for labor. The authors argued that the impact on the labor force depends on which of these effects is strongest for a given technology. In applying their model, they found that recent stagnation of labor demand is in fact explained by the acceleration of automation, coupled with fewer new tasks being generated that would require new labor. The authors cautioned that this evidence does not mean that the so-called "end of work" is imminent. Rather, they suggested that the specific ways in which technology has been recently advancing have not been advantageous to labor, because the Displacement Effect has been strongest. This is not necessarily a permanent condition, but does provide some clarity to previous conflicting results in this line of research. The authors concluded their paper by suggesting some policies that could dampen the Displacement Effect and incentivize a change in labor market dynamics.

While the current research may lack consensus with regard to the impact of technology on productivity in the economy generally, there does appear to be evidence of a boost in productivity for the manufacturing sector. With that in mind, goal of this paper is to take a closer look, and narrow the focus to the automotive manufacturing sector specifically to determine whether productivity gains are attributable to increased technology use and any effects this may have on employment levels. The goal is to essentially evaluate whether there is validity to the hypothesis of "automating jobs away" using evidence from Ohio autoworkers. Data for this project comes from the NBER-CES Manufacturing Industry Database. This data set was constructed as a joint effort between the National Bureau of Economic Research (NBER) and the

U.S. Census Bureau's Center for Economic Studies (CES), and contains data on employment, capital investments, productivity, and a host of other measures for the manufacturing industry. This data is at the national level, and has been utilized in other prominent literature in this area of study. For state level measures, some data was drawn from the U.S. Bureau of Labor Statistics (BLS). The This paper focuses on the time period from 1990 to 2011, as this is the period for which the overlap of the two datasets contains the most complete data.

Data – Construction, Sources, and Associated Assumptions

Before describing the econometric model and empirical methodology, it is important to note a few key items about the construction of the dataset. As previously mentioned, the NBER-CES Database contains a wealth of information on a variety of variables within the manufacturing industry. However, this data is at the national level, and therefore not appropriate for analysis of one state; at least, not in its given form. The substantial degree of data specificity required here – employment levels and output measures, by industry, preferably at a geographical level below state-wide – is not readily available from standard aggregators. As such, adjustments have been made to the initial dataset the geographic distribution of certain variables.

The BLS dataset features employment levels for Ohio in total and for 12 specific Metropolitan Statistical Areas (MSAs). However, as previously noted, the data specificity (i.e., the ability to break down figures by industry) needed here is not readily available at this level. In order to correct for this issue, figures were estimated based on state and MSA shares of certain variables. For instance, manufacturing employment levels are available by MSA, but there is no breakdown that provides the portion of these employees that are in the *automotive* manufacturing sector. In order to estimate this figure, Ohio's share of national manufacturing in a given year was multiplied by the national level of employment in automotive manufacturing in that same year. This yields an estimate of the number of people employed in this industry in the state within that year. This process is then repeated, but comparing MSA level data to the newly generated state-level measures. The result is an estimation of each necessary variable for each MSA in each year – a complete data set. This process was implemented primarily for the variables of employment, investments, and shipments in order to ensure that measures of these most important variables existed for all of the geographic regions. Naturally, this does present some limitations and assumptions into the model. The methodology assumes that the Ohio's share of automotive manufacturing labor is similar to its share of overall manufacturing labor. In addition, the assumptions extend down further, as it is assumed that each MSA's share of statewide automotive manufacturing employment resembles its respective share of statewide manufacturing employment. It could be true that, this is not the case; auto manufacturing could be distributed in a different manner due to various factors. Without the exact data, it is difficult to know for certain either way. However, this method of distribution is based on the best information available. Sound data exists for overall manufacturing employment in each MSA; this is the only level of data available. Given this, the method used in this paper to assess the respective proportion of that employment that is dedicated to automobile production is based on the most reliable information attainable, and the principle used to determine this distribution appears to be the most reasonable.

The NBER-CES database contains not only data for manufacturing as a whole, but allows users to be more specific and pull data just for specific kinds of manufacturing. This is because the data is sorted according to North American Industry Classification System (NAICS) codes. NAICS codes are simply a number assigned to an industry that allows for an easy means of organizing and classifying data according to industry. The codes range from two to six digits, with each additional digit adding a greater degree of specificity. For instance, NAICS codes 31 through 33 represent manufacturing, whereas 336 represents Transportation Equipment Manufacturing specifically. For this paper, data was taken from NAICS 3361, Motor Vehicle Manufacturing, and 3363, Motor Vehicle Parts Manufacturing. These codes were selected because they strike a fair balance between being too granular or too broad. Using a more specific NAICS code was considered, but doing so eliminates a large number of firms – for instance, using a code that is specific to the final assembly of cars excludes firms that build transmissions. By the same token, expanding the selection includes a number of firms who create products that are not a part of what is traditionally thought of when conceptualizing auto manufacturing – for example, NAICS 3362 includes trailer assembly, which distorts the intended focus of this paper. Figure 1 Illustrates this concept. For example, if one were to select NAICS 336111, Automobile Manufacturing, the strict definition of this code would mean that nearly every notable automotive industry would be excluded – only 3 to 4 assembly plants in the state would be included (Honda, FCA, Ford, GM, and Navistar).

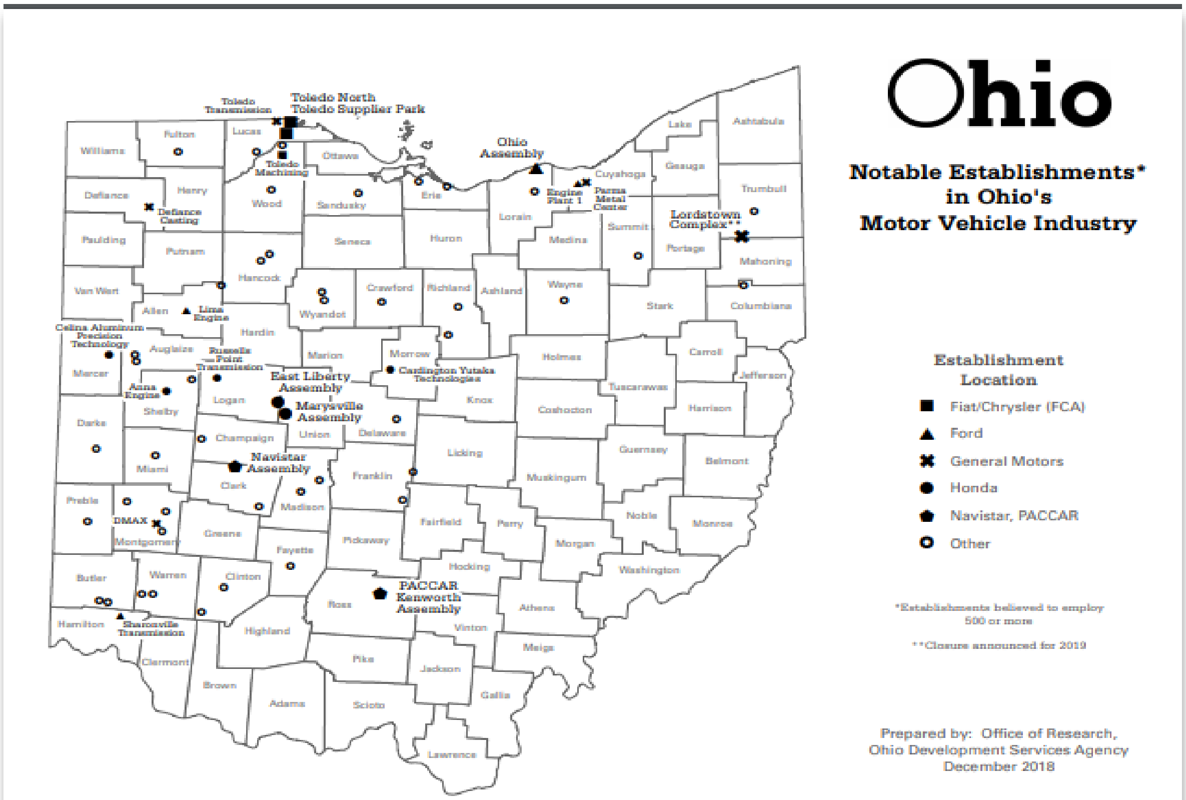


Figure 1 – Notable Establishments in Ohio's Motor Vehicle Industry (Figure prepared by the Ohio Development Services Agency, December 2018)

These codes allow the analysis to focus squarely on the key components of automotive manufacturing. It is important to discuss the details of the data here, for this plays an important role in determining the results of the analysis. Referring back to the example from Figure 1, it is clear that an overly specific choice of industry – one that effectively restricts data to four main facilities - would paint an incomplete or inaccurate picture. The broadest possible NAICS codes were used, and for good reason. Broadening the selection does not necessarily increase the number of observations. This is due to the previously discussed fact that the observations are according to MSA. No matter how many NAICS codes are chosen to include, there is still only one observation per MSA per year. However, a broad selection of NAICS codes still allows for more representative results, because it effectively includes a greater portion of all firms whose production is somehow tied to the end product of an automobile. Even with the same number of observations, we effectively see a more representative picture of the automotive production landscape. NAICS 3361 and 3363 are well-suited for this purpose.

Empirical Strategy

A model loosely based on the structure used by Acemoglu et al (2014) will be used. The model is constructed as follows:

$$Y_t = \beta 0 + \beta 1FE + \beta 2TI + \beta 3Pro + \beta 4NatAUto + \beta 5ME + \varepsilon$$

The variable descriptions are as follows:

Y – Employment, measured in thousands

β_1 – This variable represents a fixed-effect for MSA, necessary because of the structure of the dataset.

β_2 – This is the variable of interest. It represents the technology intensiveness of a firm, or how much their production relies on technology. It is measured as a ratio of capital expenditure on machines and equipment to total capital expenditure, therefore illustrating how production depends on technology.

β_3 – This variable represents productivity. It is effectively measured as output per worker, calculated by dividing the value of total shipments (units of output) by the number of employed workers. The shipment value is controlled for inflation, with 1997 dollars as the base year.

β_4 – This variable represents the number of individuals employed in the industry at the national level. The idea behind this variable is that it helps to serve as a control for national employment trends in the industry, therefore helping to isolate the effect in Ohio.

β_5 – This is the total manufacturing employment (for all manufacturing industries) in the MSA; this serves to control for other economic conditions that would effect employment in the MSA, which helps to isolate the effect of technology and machinery on employment.

<u>Trends, Results, and Analysis</u>

The following graphs help to give a visualization of some of the general trends in the data. Figure 2 shows the movement of employment in automotive manufacturing in Ohio.

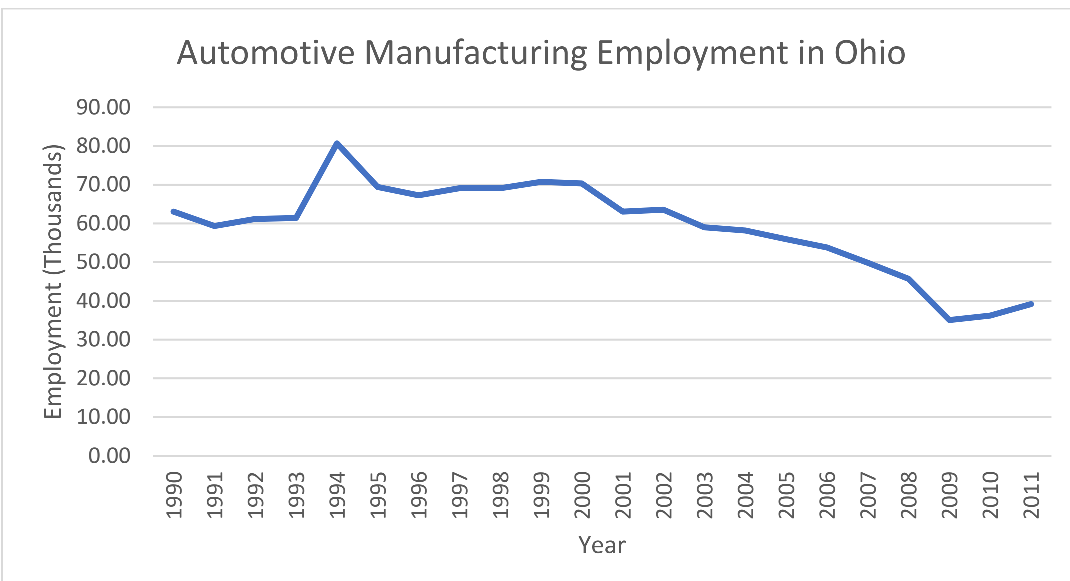


Figure 2 – Total Automotive Manufacturing Employment in Ohio, 1990-2011

This graph shows total employment in the state; this graph is total employment in the state, rather than being broken down by MSA as the regression analysis is. However, this figure still helps to visualize the overall trends in employment. Employment is relatively stable, until approximately 1999 to 2000. At this point, a decline begins that generally persists throughout the rest of the time period. This is somewhat consistent with what one may expect if the hypothesis of automation-driven job loss were true, though the lack of any decline through the 1990s may be somewhat inconsistent with that idea. Figure 2 provides some early insight, but is not particularly telling in and of itself.

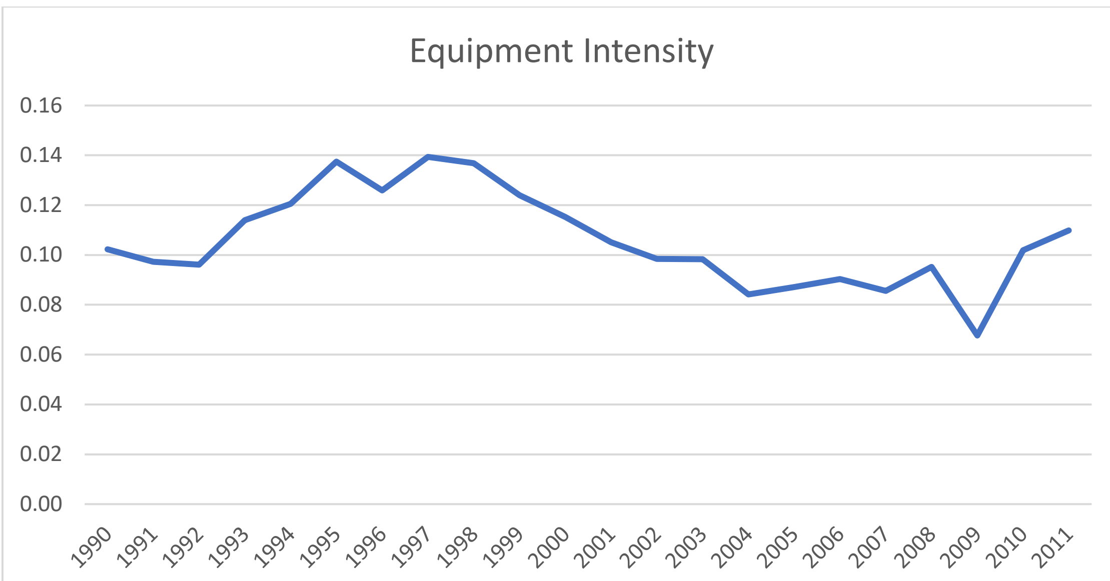
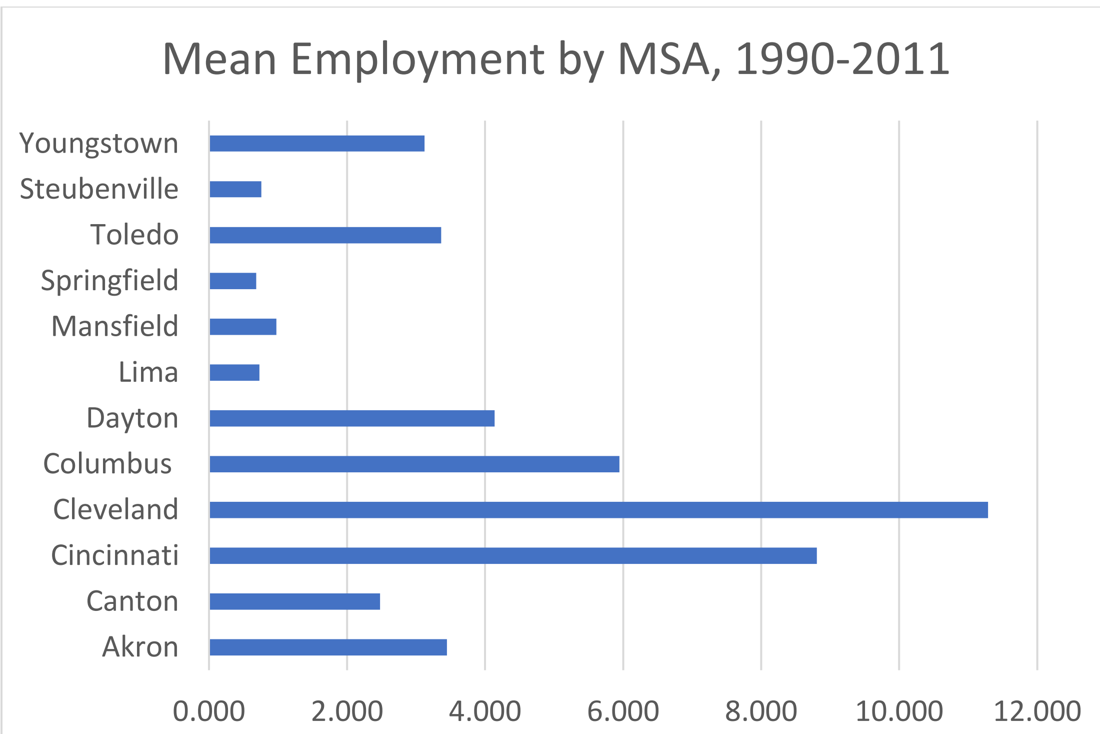


Figure 3 – Equipment Intensity, 1990-2011

Figure 3 shows the trend of equipment intensity across the given time period. This figure again presents data at the State level, for ease of viewing. The picture here is perhaps surprising – intensity peaks in the late 1990s, and then actually begins a decline before somewhat leveling off around the time of the Financial Crisis. This would seem to indicate that Ohio auto manufacturing firms actually became less dependent on technology and machinery over time.

Such a result would go against nearly every intuition one would have, particularly as technology appears to play an increasing role in our daily lives – imagine for instance attempting to exist for a week without smartphone access. Of note is that the decline in equipment intensity begins around the year 2000. This could potentially align with several of the findings from Acemoglu, which pointed out that productivity gains from technology began to slow around 2000, as well as a slowdown in employment losses around the same time (2014). Though this paper is focused on a more specific portion of manufacturing than Acemoglu, this relation merits mentioning. However, mere trends in technology usage are not conclusive in and of themselves.



MSA	Mean Employment (Thousands)
Akron	3.446
Canton	2.476
Cincinnati	8.806
Cleveland	11.287
Columbus	5.947
Dayton	4.138
Lima	0.729
Mansfield	0.979
Springfield	0.683
Toledo	3.366
Steubenville	0.757
Youngstown	3.121

Figure 4, Mean Employment by MSA, Tabular & Graphical

Figure 4 gives an overview of employment by Metropolitan Statistical Areas. It shows the mean employment across the time period, measured in thousands. There are no real surprises here; in general, larger cities are shown to have the largest shares of employment, generally speaking. This is logical on theoretical grounds, but is particularly unsurprising given the methodology of this paper. As previously mentioned, the number of individuals employed in auto manufacturing in a given MSA is estimated; this is done by calculating the share of statewide manufacturing employment that the MSA is responsible for, and estimating that the same share of statewide *automotive* manufacturing employment is located in the MSA. Thus, the distribution of auto manufacturing employment necessarily follows overall manufacturing employment. These means do not reveal the full picture, but it is again helpful to gain introductory insight.

Year Range	Mean Employment	Shipments/Worker	Captial Equipment Ratio
1990-1997	3.871271148	431.8073397	0.095165847
1998-2004	3.858367831	436.2071688	0.10611878
2005-2011	3.813506794	650.0699071	0.105619663

Figure 5, Comparison of Means

Figure 5 allows for a more complete view of the reality. The figure splits the data into three time periods, to allow for a visualization of how key variables are moving over time, and perhaps hint at how they could potentially influence one another. The Year Ranges are not chosen for any specific reason; they are simply set up to split the data into 3 sections as evenly as possible. The Mean Employment column shows mean employment across all MSAs. Shipments/Worker represents the measure of productivity; as previously noted, it is measured as the deflated value of shipments divided by the number of individuals employed. Simply put, it is a measure of output per worker. Capital Equipment Ratio is the measure of technology dependence – the aforementioned “equipment intensity”, a ratio of the amount of capital expenditure on machines and equipment compared to overall capital expenditure. The figure reveals important trends for each variable. Employment is shown to be decreasing, as revealed by Figure 2. Productivity (Shipments/Worker) experiences a small increase between the first two time periods, and then experiences substantially larger growth from the second time period to the third. The Capital Equipment ratio provides a sense of numerical magnitude to the trend revealed by Figure 3; equipment intensity slightly rises, but then experiences a general decline or stagnation. Overall, the insight gained from this figure is mixed. While employment and productivity seem to be moving in a way that would be consistent with the automation hypothesis, the declining technology investment renders this somewhat inconclusive. From this view, it could still be possible that technology is responsible for the overall decline in employment, but such a conclusion is anything but clear. Furthermore, the magnitudes of change appear to be incredibly small, particularly for employment and equipment intensity (technology dependence). These minor changes do not allow for a clear projection of whether the changes are significant in a statistical sense. However, this general overview of variation gives the most comprehensive conception of the data and variable relationships thus far. With these somewhat inconclusive results in mind, we proceed to the regression analysis.

Regression Results

Table 1 shows the results of a preliminary regression. The results below show the impact of increased technology usage on productivity. As expected, it is shown that increasing technology usage has generated greater productivity, controlling for several key variables. The results are significant at the 1% level. This is not a surprising result, as it matches intuition and is also found in various other research papers on general manufacturing. Even though this regression is not the main focus of the paper, and the results may seem somewhat obvious, it is still worth including for a few key reasons. First, this result is not necessarily universal in the literature. For instance, Acemoglu, et al, found somewhat mixed evidence for technology-driven

Productivity	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Technology and Equipment Intensity	1071.643	368.2762	2.91	0.004	349.8354	1793.451
Manufacturing Employment in MSA	-7.143418	.887638	-8.05	0.000	-8.883157	-5.40368

National Auto Employment	-.670169	.0439938	-15.23	0.000	-.7563953	-.5839427
MSA Auto Employment	106.7584	13.43163	7.95	0.000	80.43286	133.0839
_cons	972.3147	34.86205	27.89	0.000	903.9864	1040.643

Table 1, Productivity Returns from Technology Use

productivity growth (2014). In light of that, it helps to check if that evidence exists here. Additionally, the very basis of the hypothesis examined in this paper – that technology is effectively automating jobs away – relies heavily on the assumption that technology allows for greater productivity in automotive manufacturing. If in fact, there were no evidence that technology use boosts productivity, there would not be much incentive for firms to replace workers with machines. At that point, there would have to be a significant cost advantage for firms to do so. Therefore, by running this regression, it is shown that the hypothesis is at least possible. This evidence basically lays the groundwork for the key regression, by proving that it is at least possible or reasonable to think that technological advancement is having some impact on employment.

MSA Auto Manufacturing Employment	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]

Technology and Equipment Intensity	-2.479881	1.544664	-1.61	0.108	-5.507367	.5476063
Productivity	.0018368	.0002311	7.95	0.000	.0013838	.0022897
National Auto Manufacturing Employment	.0020347	.0002171	9.37	0.000	.0016091	.0024602
MSA Total Manufacturing Employment	.0658922	.0004263	154.56	0.000	.0650566	.0667278
_cons	-2.492087	.2444014	-10.20	0.000	-2.971105	-2.013069

Table 2, Impact of Technology on Automotive Manufacturing Employment

Table 2 displays the results for the main regression of interest. Technology intensity is shown to negatively correlate with employment. However, what is notable is the significance. This relationship cannot be said to be statistically significant. It is nearly so at the 10% level, but still not enough to merit evidence of causality. This would indicate that there is no evidence that technological improvement is a driver of employment declines – simply put, automation is not chiefly responsible for declining employment levels in automotive manufacturing in the state of Ohio. An interesting finding is the impact of productivity, which is shown to have a slight positive impact on employment. In itself, this is entirely expected. However, it is interesting to note that, even though technology increases productivity, and productivity has a significant positive relationship with employment, the relationship between technology and employment does not carry over.

Conclusion

Overall, the findings indicate that there is no evidence that increasing use of technology in the production process decreases employment. Technology is a driver of productivity, as expected. But, the overall hypothesis of automation as a job killer cannot be substantiated, at least for automotive manufacturing in Ohio. This finding would appear to fall in line with the results of the *Return of the Solow Paradox?* paper, which found mixed productivity growth associated with technological advancement, but no real evidence of automation as a job killer for the overall manufacturing sector. This paper effectively extends these results to a more specific geographical and industrial focus.

It is possible that these findings are the result of problems in the model. In light of that, there are a few key areas in which this model could be improved, or the research extended to fully vet the validity of these results. Potentially, the measure of technology usage – the ratio of capital expenditure on machinery to total capital expenditure – is flawed. Perhaps a better measure exists that could more accurately capture the relationship between technology use and employment. Changes to the technology measure was shown to have an impact in previous papers, and although the measure here is based on other empirical papers, it is nonetheless possible that this measure could be improved. Certainly, this presents an opportunity to re-evaluate the claims of this paper to effectively check the results. On a final note, assuming the results of this paper are an accurate depiction of reality, one specific variable likely holds the explanation as to why it cannot be said that technology use hurts employment. The results from Figure 3, which showed the change in technology dependence over time, could be the reason for these findings. It was shown that technology usage actually became a smaller part of capital investment in a relative sense over the time period studied here. This fact is potentially a key determinant of the overall findings. Simply put, whatever the reason that firms have become less dependent on technology, it is likely an important part of the relationship between technology and employment. However, at this point, it appears that claims of humans losing the “race against the machine” may be somewhat premature.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G., & Price, B. (2014). Return of the Solow Paradox? IT, Productivity, and Employment in U.S. Manufacturing. *American Economic Review*, *104*, 394–399. doi: 10.3386/w19837

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, *33*(2), 3–30. doi: 10.1257/jep.33.2.3

Brynjolfsson, E., & McAfee, A. (2012). *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington: Digital Frontier Press.

Fleck, S., Glaser, J., & Sprague, S. (2011). The Compensation -Productivity Gap: A Visual Essay. Retrieved from https://www.bls.gov/opub/mlr/2011/01/art3full.pdf